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"THE GENDER PRODUCTIVITY GAP. SOME EVIDENCE FOR A SET OF HIGHLY PRODUCTIVE ACADEMIC ECONOMISTS"

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Abstract

This paper compares the average productivity of males and females in a set of 2,530 highly productive economists that work in 2007 in a selection of the top 81 Economics departments worldwide. The main findings are the following. Firstly, after controlling for age and cohort effects, as well as for the effect of four career variables and a variable on geographic mobility, the productivity of females is, on average, 54% lower than the productivity of males. Secondly, the gender productivity gap decreases as we move up from the departments outside the U.S. towards the top ten U.S. departments. Thirdly, when we restrict our attention to the 833 economists with above average productivity, the proportion of females decreases from 14.0% to 5.4% and, after controlling for demographic and career variables, the gender productivity gap decreases to 15.8%.

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I. INTRODUCTION

We are indebted to Robert Merton (1957), the founder of the modern sociology of science, for the recognition of the crucial role of the priority of discovery in the reward structure in science. Publication – a necessary step in establishing priority – is a lesser form of recognition within the reach of most scientists. As indicated by Van Raan, one of the leading researchers in scientometrics, there is little doubt that scientists who have something important to say "*do publish their findings vigorously in the open international journal ('serial') literature… The daily practice of scientific research shows that inspired scientists in most cases … 'go' for publication in the better and –if possible– the best journals*" (Van Raan, 2004, p. 26; 2005, p. 134). Therefore, everybody's research efforts become observable through publication and citation counts. Consequently, it has been argued that an advantage of using scientists as an object of study is that information about research productivity is available through bibliographic databases (Coupé *et al.*, 2006).

The productivity of individual scientists has been studied extensively since Lotka's (1926) pioneer contribution, in which the probability of an author publishing a certain number of articles in Chemistry was estimated to be an inverse square function of the number of publications. Recent results using a large dataset of 17.2 million disambiguated authors confirm that individual productivity distributions –measured by the number of publications and mean citations per author in the period 2003-2011–, are not only highly skewed, but also very similar across 30 broad scientific fields (Ruiz-Castillo & Costas, 2014).

On the other hand, there is a substantial body of empirical research that attempts to pin down the determinants of scientific productivity for individual researchers (see *inter alia* Levin & Stephan, 1991, Hall *et al.*, 2007, and Combes & Bosquet, 2013). In particular, since Cole & Zuckerman (1984) many studies have documented the existence of a gender productivity puzzle indicating that female scientists publish much less than their male counterparts (Nielsen & Elkjaer, 1984, Long, 1990,1992, Kyvic, 1990, Long *et al.*, 1993, Kyvic & Teigen, 1996, Xie & Shauman, 1998, Prpic, 2002, and Fox, 2005).

However, there are few academic studies on what drives top research productivity. In this paper. We study the gender productivity gap in a set of 2,530 highly productive economists that work in 2007 in the top 81 Economics departments worldwide according to the Econphd (2004) ranking. We measure individual productivity in terms of a quality index that weights the number of publications from the beginning of everyone's career up to 2007 in four equivalent journal classes. We begin by observing that the unconditional productivity gap between the genders is very large indeed: the average productivity of females –representing 14% of the total sample– is approximately 100% lower than the average productivity of males. From here, we find it useful to proceed in four steps.

1. Our measure of aggregate productivity up to 2007 favors older people. Therefore, it is essential to control for experience or (academic) age effects. In addition, we study cohort effects for a distinction between young and older individuals. Since females are considerably younger than males, after controlling for age and cohort effects the gender productivity gap becomes 54.7%.

2. We have information on two more types of covariates: a relatively rich set of career variables, namely, the university where each individual earns her B.A., her Ph.D., the university where each holds her first job, and the university where each is working in 2007, as well as some information on geographic mobility. Interestingly, the distribution of males and females over these five variables is very similar. Consequently, after controlling for them the overall gender productivity gap is barely affected and becomes 53.5%.

3. In a companion paper with Pedro Albarrán, we document the existence of *department effects* in the U.S., in the sense that the average productivity of economists working in each of the three department categories defined above is hierarchically ordered (Albarrán *et al.*, 2016). In the present context, we find it interesting to investigate whether the gender productivity gap is constant across department categories, and between foreigners and stayers. The answer is thatn the gender productivity gap decreases as we move from the bottom to the most prestigious U.S. departments.

4. In Albarrán *et al.* (2016) we found it instructive to make productivity comparisons not only for the entire population consisting of 2,530 economists, but also for an elite consisting of 833 individuals with above average productivity. Furthermore, given the high degree of skewness of individual productivity, restricting attention to what happens at the upper tail of the distribution is always an interesting research option. In our case, we find that the average productivity of females –representing 5.4% of the total sample– is 15.8% lower than the productivity of males.

The rest of the paper consists of three Sections. Section II presents the data as well as the empirical results comparing the productivity of males and females, in the total sample and the elite, controlling for demographics, career, and geographic mobility variables. Section III summarizes the results.

II. DATA, AND EMPIRICAL RESULTS

II.1. The data

In this Sub-section, we briefly describe the dataset. Further details can be found in Albarrán *et al.* (2014, 2016). In the first place, we select faculty members in the top 81 departments worldwide according to the Econphd (2004) university ranking. In all sciences, researchers originate from many countries. However, when we focus on the most productive and influential scholars we observe that a large contingent of scientists working in the top U.S. research institutions have obtained their first college degree in their country of origin.[1] Hence, not surprisingly, 52 out of the 81 departments in our sample are located in the U.S. We find it convenient to partition the U.S. departments into three categories: the top 10, the next 15, and the bottom 27 departments.[2] On the other hand, there are only eleven countries with at least one of the

[1] See *inter alia* Ioannidis (2004), Bauwens *et al.* (2008), and Panaretos & Malesios (2012). For a detailed analysis of the characteristics of highly productive researchers in economics, see our companion paper Albarrán *et al.* (2014).

[2] Of course, which departments are in the "top 10", "top 25" or "last 27" at any moment is open to debate. Moreover, even if this classification is appropriate for the period 2004-2007, individual departments are likely to have changed positions over the period of this study prior to 2007. Therefore, it is advisable to take this partition as representative of "top" or "bottom" departments in general.

remaining 29 non-U.S. departments in the sample.[3] We refer to them as the Other Sample Countries (OSC hereafter).

Searching in the 81 departmental web pages in 2007, we found a total of 2,705 economists with information concerning four characteristics: nationality (in terms of the country where each individual obtains a B.A.); university where a Ph.D. is obtained; academic age, namely, the number of years elapsed since earning a Ph.D. (or an equivalent degree) up to 2007, and publications in the periodical literature up to that date. Out of the 2,705 economists in our dataset, there are 175 faculty members without any publications at all (typically because they are on tenure track). In line with the previous literature on individual productivity, in the sequel we focus on what we call the *total sample* consisting of the 2,530 faculty members with at least one publication.

We distinguish between four journal classes. In our preferred weighting scheme, the four classes are assigned weights equal to 40, 15, 7, and 1 point, respectively. The resulting quality index is denoted by Q.[4] The following two characteristics of this productivity measure are worth noting. Firstly, the 2,530 individuals in the total sample are very productive: average productivity is 307.3 quality points *per capita*, equivalent to more than seven class A articles or about 20 class B articles. Secondly, the distribution of individual productivity is highly skewed: the average productivity is 17 percentage points above the median, and the top 11.5% in category 3 account for 43.6% of all quality points.

[3] The countries are the UK, the Netherlands, Spain, Sweden, France, Germany, Belgium, and Denmark in Europe, and Canada, Israel, and China elsewhere.

[4] Classes A, B, and C consist of 5, 34, and 47 journals, while class D consists of any other journal. Class A includes the *American Economic Review*, *Econometrica*, *Journal of Political Economy*, *Quarterly Journal of Economics*, and *Review of Economic Studies*. By way of example, the following 12 journals are in class B: *Economic Journal*, *Games and Economic Behavior*, *International Economic Review*, *Journal of Econometrics*, *Journal of Economic Growth*, *Journal of Economic Theory*, *Journal of Finance*, *Journal of Labor Economics*, *Journal of Monetary Economics*, *Journal of Public Economics*, *Rand Journal of Economics*, and *Review of Economics and Statistics*. Table A in Appendix I in Albarrán *et al.* (2014) includes the listing of the 81 departments, together with information for each institution concerning the number of faculty members (including Emeritus Professors), the number of people without publications, the remaining scholars' publications in classes A to D, and the department value of the Q index. This paper also includes a listing of the 908 economists (including members from other institutions that had received a fellowship in the Econometrics Society) with above average productivity.

II.1. Results for the total sample

Given the high degree of skewness of the individual productivity distribution, in the sequel the dependent variable is always the log of the *Q* index. We begin quantifying the unconditional gender productivity gap. For that purpose, in *Model 1* we include a single dummy variable, *Female*, that takes the value one for females. As we observe in Table 1, the average productivity of females –representing 14% of the total sample– is approximately 104.4% lower than the average productivity of males.

Table 1 around here

Next, we proceed in four steps. Firstly, we analyze the important role of age and cohort effects. Secondly, we compare the overall productivity of males and females controlling for department effects in the U.S., and a number of other career variables. Thirdly, given the importance of department effects, we compare the productivity of males and females within each of the four department categories mentioned in the Introduction. In this way, we estimate four gender productivity gaps. Finally, we introduce the information on geographic mobility The definition of all explanatory variables will be presented in due order below. Descriptive statistics for both genders in the total sample are included in Table A in the Appendix, where the reference group for any set of dummy variables is marked with an asterisk.

Demographic variables

As indicated in the Introduction, our measure of aggregate productivity up to 2007 favors older people. Consequently, together with the variable *Female*, *Model 2* includes the following three variables: *Age*, $(Age)^2$, and a dummy variable, *Young*, that takes the value one for young people, defined as those who earn a Ph.D. at most 20 years before 2007. Taking into account that the median age for finishing a Ph.D. is approximately 30 (Scott & Sigfried, 2008), young people in our sample are those with at most 50 years of age in 2007. To account for the possibility that the productivity effect of one more year of academic experience is different for young and older individuals, our specification includes an interaction between the cohort and the age variables.

As can be observed in Table 1, the six variables of Model 2 are highly significant. Age and cohort effects for individuals of different age are estimated in Section III.1 in Albarrán *et al.* (2016). Here, it suffices to note the following four points. Firstly, in agreement with human capital models, we find a humped-shaped progression of individual research productivity with academic age because the stock of human capital needs to be built up at the beginning of the career while, due to the finiteness of life, no new investment offsets depreciation and net investment declines (eventually) over time. Secondly, the young are more productive than the old, and the productivity gap of the younger individuals increases with experience. Thirdly, since the females are much younger than the males (see the first two rows in the Appendix), the gender productivity gap in Model 2 is reduced to 57.9%. Finally, age, cohort, and gender effects account for a large proportion of the variance: the adjusted R^2 in Model 2 is 0.44.[5]

Males versus females: a first approximation

Together with demographic variables, in *Model 3* we include a set of dummy variables that capture four new variables: the university where individuals obtain their B.A., their Ph.D., where they held their first job, and where they work in 2007. The distribution of males and females in the total sample according to these career variables is in Panels A to D in the Appendix. Regression results for Model 3 are in Table 1.[6]

For our purposes, the most important point is the existence of strong department effects in the U.S. (*p*-values are available on request). On the other hand, note that the productivity of economists in the last 27 U.S. departments is indistinguishable from the productivity in the last 29 OSC departments (*t*-value equal to

[5] Essentially, the same results are obtained when young people are defined as those who earn a Ph.D. at most 15 or 24 years before 2007 (Albarrán *et al.*, 2016).

[6] All regressions in the sequel include clustered standard errors by the university where each individual works in 2007.

1.6). In view of the fact that these two groups are heterogeneous categories with a large overlap in terms of the Econphd department ranking (see the details in Albarrán *et al.*, 2016), this result is not surprising.

The existence of department effects in the U.S. requires discussing whether higher performing universities contribute to the productivity of individual researchers and/or whether they simply attract more productive individuals. It should be recognized at the outset that department effects (and indeed the rest of our productivity comparisons) are obtained with retrospective data concerning economists' career mobility and aggregate productivity up to 2007. Thus, the endogeneity of individuals' locational choice makes a causal interpretation of our results impossible. However, as discussed in detail in Albarrán *et al.* (2016), the literature concerning the inexistence of geographically based spillover effects (Han Kim *et al.*, 2009, Azoulay *et al.*, 2010, Waldinger, 2012, Borjas & Doran, 2014, and Dubois *et al.*, 2014) leads us to suggest that department effects are essentially due to self-selection on the supply side, and the role of meritocratic criteria on the demand side of a highly competitive market.

Be that as it may, the lesson is that it is advisable to make productivity comparisons between males and females within each department category. This is what we do in *Model 3'*. Regression results for the key variables are presented in Panel A in Table 2 (to save space, results for the control variables are available on request). In turn, estimated gender productivity gaps and *p*-values are in Panel B in Table 2.

Male productivity is significantly greater than female productivity in the four department categories. However, gender productivity gaps decrease as we move up from the last 27 to the top 10 U.S. departments. On the other hand, gender gaps in the bottom U.S. category and the OSC departments are of the same order of magnitude.

Table 2 around here

The final specification

Finally, in *Model 4* we incorporate the information on geographic mobility. In the OSC, we distinguish between three groups: those who study and/or work abroad followed by a return to the home country (*brain circulation*); those who conduct their entire careeer in the same country (*stayers*), and those working in 2007 in a country different from their country of origin (*brain drain*). Since brain circulation in the U.S. is a very limited phenomenon affecting only eight economists, among those working in 2007 in that country we distinguish only between U.S. stayers and U.S. brain circulation on the one hand, and migrants on the other hand. Regression results for Model 4 in Table 1 warrant two comments. Firstly, as in Albarrán *et al.* (2016), department effects in the U.S. are present for both stayers and foreigners. Secondly, the overall gender productivity gap is practically equal to what we found in Model 3.

On the other hand, in *Model 4'* we investigate gender productivity gaps within brain circulation in the OSC, and migrants and stayers in all department categories. As before, regression results for the key variables are presented in Panel A in Table 2, whereas estimated gender productivity gaps are in Panel B in Table 2. The adjusted R^2 in Model 2 is 0.56. We emphasize the following three points.

• The smallest productivity gap is found for stayers at the top 25 U.S. departments. As a matter of fact, in the top 10 U.S. departments the productivity of females is indistinguishable from the productivity of males.

• Brain drain economists in the U.S. and OSC brain circulation have an intermediate productivity gap. The gap for foreigners in the OSC is only slightly smaller.

• The largest gaps are found for the stayers at the bottom in the two geographical areas.

II.3. Results for the elite

Females only represent 5.4% of the 833 elite economists with above average productivity. Given the small size of many of the original groups distinguished in the total sample, the partition of all career variables must distinguish now between more aggregate categories. In particular, geographic mobility variables must be abandoned. Descriptive statistics are in Table B in the Appendix.

Intuitively, increasing the quality threshold and reducing the sample size would tend to make elite members more homogeneous among each other in all dimensions. The main results in the gender dimension can be summarized in the following three points.[7]

1. As can be observed in Panel A in Table 3, the unconditional overall gender productivity gap in the equivalent of Model 1 is reduced to 24.4%.

2. The proportion of young people decreases: relative to the total sample, older people are overrepresented in the elite. Nevertheless, the females are still younger than the males. The distribution of both genders over the career variables is again very similar. At any rate, after controlling for demographic and career variables in the equivalent of Model 3, the overall gender productivity gap becomes 16.5%.

3. In the equivalent of Model 3' in Panel B in Table 3, the overall gender productivity gap is only significant –and of the same order of magnitude– in the top 10 U.S. departments and the OSC. In the remaining 32 U.S. departments, the productivity of both genders is indistinguishable.

Table 3 around here

III. SUMMARY OF RESULTS AND CONCLUDING COMMENTS

III.1. Summary

This paper has analyzed the gender productivity gap for two samples: 2,530 highly productive economists working in 2007 in 81 of the top economics departments in the world, and an elite consisting of 833 researchers with above average productivity. The main results can be summarized as follows.

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[7] The only observation with a missing value in the first job variable is eliminated from the analysis.

1. The unconditional gender productivity gap in the total sample for an aggregate measure of productivity based on the number of publications up to 2007 is very large. However, after correcting for age and cohort effects, this overall gap is reduced to 54.7%. Since the distribution over four career variables and a variable on geographic mobility is similar for both genders in the total sample, the overall gap controlling for these covariates remains essentially stable.

2. Given the importance of department effects, it is advisable to break down the overall gender productivity gap into the gaps estimated in each of four department categories. The key result is that the productivity gap in the total sample decreases as we move up towards the most prestigious U.S. departments. In particular, among the stayers in the top 10 U.S. departments –which represent 9.2% of the population– the productivity of females is indistinguishable from the productivity of males. The largest productivity gaps are found at the last 27 U.S. departments and the 29 OSC departments, which represent 64.6% of the population.

3. When we restrict our attention to the 32.9% of the population with above average productivity, the proportion of females decreases from 14.0% to 5.4%. The more important result in this case is that, after controlling for demographic and career variables, the gender productivity gap decreases from 53.5% in the total sample to 15.8% in the elite. Finally, the productivity of females is indistinguishable from the productivity of males in the last 42 U.S. departments representing 46.4% of the elite.

We would like to emphasize the similarity of our results to those obtained in the important contribution by Kelchtermans and Veugelers (2013) –KV hereafter–, who study top research productivity and its persistence in a unique panel of 1,036 scientists within the fields of biomedical and exact sciences from the University of Leuven, in The Netherlands, in the period 1992 to 2001. The analysis focuses on the number of publications, although KV check the robustness of the results when using citations received in a three-year window as a measure of performance. Using *k*-means clustering, KV compare for each year each scientist's performance within each of twelve scientific disciplines with colleagues who are active in that discipline. In this way, they distinguish three performance categories in each discipline: top, intermediate, and low. On average, 16% of observations are classified as a top performance, which account for 43% of all publications. This confirms the high skewness of the distribution of publications in the sample.

KV employ duration models to study the factors that influence the hazard for a researcher to achieve a first and subsequent top performance in their career, taking into account time-varying and invariant covariates and checking for the influence of past (top) performance. For our purposes, their main results can be summarized in the following three points.

1. A hazard model predicting the time toward first top performance establishes the importance of gender as a determining factor, with females being significantly less likely to reach first top performance: the hazard to become top is 2.7 times higher for males than females.

2. When analyzing subsequent top performances, KV find strong support for a cumulative process, with hazard to next top performance being significantly and (increasingly) positively affected by previous past performance. The interaction between the number of previous top performances and the gender dummy turns out to be highly significant, suggesting that the gender effect is mainly a selection problem into the first top. Once women break through to their first top performance, no gender bias hinders them in further top performances. In particular, KV show that working with larger teams increases a researcher's chances of achieving top productivity, but with a higher importance for female scientists.

3. These results are robust to corrections for unobserved individual heterogeneity. The effects of both gender and previous top performances remain sizable and significant. In addition, female scientists remain more sensitive to the cumulative advantage effect than men are: for a female researcher, each top performance increases the odds to be top again with a factor of 2.23, whereas for a male this factor is only 1.36.

III.2. Shortcomings and further research

Our study has several limitations. In the first place, we lack information on the citation impact and the co-authorship patterns that have been found to be important in other attempts to account for individual productivity differences (KV, and Combes and Bosquet, 2013). In the second place, we only have information on the productivity and characteristics of economists at a given moment in time. Therefore, we cannot investigate the cumulative advantage effect that has been emphasized since the the seminal contribution by Merton (1968) on the Matthew effect (see KV, and Azoulay *et al.*, 2014, as well as the references they provide to the limited evidence available in previous works).

On the other hand, both KV and our contribution raise several intriguing questions. Firstly, it would be interesting to investigate whether gender differences in pay for top researchers are lower than for regular scholars. Given the differences in the gender productivity gap reviewed in this note, this is what we should expect at least in countries –such the U.S.– where hiring and promotion procedures are essentially guided by meritocratic practices and competitive market forces. Secondly, the main question left unanswered is which are the characteristics that distinguish female top researchers from the remaining female scholars. The usual suspects are marital status, presence of children, and time use at home relative to spouses during the different stages of the academic career.

But there are other measurable possibilities. Leahey (2006) studies the extent to which scholars in linguistics and sociology are specialized in terms of subject matter, that is, the focus on one or a few subfields rather than spanning many. She finds that males tend to specialize more, and that the gender gap in specialization helps to account for the gender productivity gap. In turn, Dolado *et al.* (2012) study the gender distribution of research fields in economics using a dataset of 1,900 researchers affiliated to the top 50 economics departments according to the same Econphd (2004) university ranking we used in our research. Their main findings are the following three. (i) There are large differences between male and female economists in terms of research-field choices; (ii) the probability that a woman chooses a given field is positively relted to the past share of women in that field, and (iii) the female share in a given field is negatively related to an index of how competitive is that field (proxied by the proportion of papers in each field that are published in highly prestigious journals). The findings from these two papers suggest investigating whether differences in the extent of specialization and research field choice among top and regular males and females help accounting for the differences in the gender productivity gap documented in this note.

APPENDIX

Table A. Explanatory variables. Descriptive statistics in the total sample

	MALES		FEMALES	
Mean *Age* (Standard deviation)	19.75 (12.5)		12.96 (9.99)	
Cohort, % *Young*	54.7%		78.9%	
A. UNIVERSITY OF B.A.	**Frequency**	**%**	**Frequency**	**%**
1. *Top 10 U.S.*	261	12.0	38	10.7
2. *Next 15 U.S.*	122	5.6	22	6.2
3. *Next 27 U.S.*	118	5.4	16	4.5
4. *Other U.S.*	347	16.0	56	15.8
5. *EU*[a]*	807*	37.1	141	39.7
6. *RW*[b]	520	23.9	82	23.1
Total	**2,175**	**100.0**	**355**	**100.0**
B. UNIVERSITY OF Ph.D.				
1. *Harvard* **&** *MIT*	305	14.0	47	13.2
2. *Other Top 10 U.S.*	649	29.8	100	28.2
3. *Next 15 U.S.*	353	16.2	63	17.7
4. *Next 27 U.S.*	157	7.2	24	6.8
5. *Other U.S.*	45	2.1	7	2.0
6. *EU*[a]*	584*	26.9	96	27.0
7. *RW*[b]	82	3.8	18	5.1
Total	**2,175**	**100.0**	**355**	**100.0**
C. UNIVERSITY OF FIRST JOB				
1. *Top 10 U.S.*	472	21.6	66	18.6
2. *Next 15 U.S.*	319	14.6	50	14.1
3. *Next 27 U.S.*	305	14.0	58	16.3
4. *Other U.S.*	142	6.5	32	9.0
5. *EU*[a]*	589	27.3	93	19.2
6. *RW*[b]	338	15.5	53	26.6
7. *Missing*	10	0.5	3	0.8
Total	**2,175**	**100.0**	**355**	**100.0**
D. UNIVERSITY OF CURRENT JOB & GEOGRAPHIC MOBILITY				
1. ***Top 10 U.S. departments***	**362**	**16.7**	**44**	**12.7**
Stayers & Brain circulation	200	9.3	28	8.2
Foreigners	162	7.4	16	4.5
2. ***Next 15 U.S. departments***	**414**	**19.0**	**73**	**20.6**
Stayers & Brain circulation	240	11.0	41	11.5
Foreigners	174	8.0	32	9.1
3. ***Last 27 U.S. departments***	**574**	**26.3**	**100**	**27.9**
Stayers & Brain circulation	360	16.5	54	14.9
Foreigners	214	9.8	46	13.0
4. ***29 OSC departments**** in Model 3	**825***	**37.9**	**138**	**38.9**
Brain circulation	158	7.3	23	6.5
*Stayers** in Model 4	359*	16.5	52	14.6
Foreigners	308	14.1	63	17.8
Total	**2,175**	**100.0**	**355**	**100.0**

Table B. Explanatory variables. Descriptive statistics in the elite

	MALES		FEMALES	
Mean *Age* (Standard deviation)	27.44 (12.5)		23.64 (9.99)	
Cohort, % *Young*	27.5%		48.9%	
A. UNIVERSITY OF B.A.	**Frequency**	**%**	**Frequency**	**%**
1. *Top 25 U.S.*	203	25.7	14	31.1
2. *Other U.S.*	189	24.0	13	28.9
3. *Other countries*	396*	50.3	18	40.0
Total	**788**	**100.0**	**45**	**100.0**
B. UNIVERSITY OF Ph.D.				
1. *Harvard* **&** *MIT*	170	21.6	8	17.8
2. *Other Top 10 U.S.*	148	31.5	25	55.6
3. *Rest of U.S. and other countrie**	470*	46.9	12	26.6
Total	**788**	**100.0**	**45**	**100.0**
C. UNIVERSITY OF FIRST JOB				
1. *Top 10 U.S.*	270	34.3	21	46.7
2. *Other U.S.*	269	34.2	11	24.4
3. *Other countries**	248*	31.4	13	28.9
4. *Missing*	1	0.1	0	0.0
Total	**788**	**100.0**	**45**	**100.0**
D. UNIVERSITY OF CURRENT JOB				
1. *Top 10 U.S. departments*	238	30.2	14	31.1
2. *Next 15 U.S. departments*	187	23.7	18	40.0
3. *Last 27 U.S. departments*	174	22.1	8	17.8
4. *29 OSC departments**	189*	24.0	5	11.1
Total	**788**	**100.0**	**45**	**100.0**

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Table 1. Overall gender productivity gap. A sequence of models for the total sample

Dependent variable: Log *Q*

	MODEL 1		MODEL 2		MODEL 3		MODEL 4	
	Coeff.	***t*-value**	**Coeff.**	***t*-value**	**Coeff.**	***t*-value**	**Coeff.**	***t*-value**
Female	-1.044	-9.7*	-0.5474	-7.3*	-0.5355	-7.1*	-0.5409	-7.2*
Constant	5.0615	62.8*	2.6462	13.9*	2.0037	11.3*	1.9095	10.2*
CONTROL VARIABLES								
A. Demographic variables								
1. *Age*			0.1397	10.9*	0.1618	15.2*	0.1634	15.2*
2. Age^2			-0.0014	-5.3*	-0.0019	-8.8*	-0.0019	-8.9*
3. *Young* x *Age*			0.2108	8.4*	0.2239	10.5*	0.2229	10.6*
4. *Young* x Age^2			-0.0081	-7.8*	-0.0089	-10.2*	-0.0088	-10.3*
5. *Young*			-0.3771	-2.8*	-0.3555	-3.1*	-0.3637	-3.2*
B. University of B.A.								
1. *Top 10 U.S.*					-0.0787	-1.0	0.1537	0.8
2. *Next* 15 *U.S.*					-0.1943	-1.7	0.0306	0.2
3. *Next 27* U.S.					-0.0876	-0.8	0.1889	1.0
4. *Other U.S.*					-0.1839	-2.3	0.0734	0.4
5. Reference group = *EU*								
6. *RW*					0.0816	1.1	0.0561	0.7
C. University of Ph.D.								
1. *Harvard* & *MIT*					0.3565	3.7*	0.2590	3.0*
2. *Other Top 10 U.S.*					0.1736	2.0*	0.0719	0.9
3. *Next* 15 *U.S.*					0.1880	1.9	0.0833	0.9
4. *Next* 27 *U.S.*					-0.0720	-0.0	-0.1045	-0.9
5. *Other U.S.*					-0.0740	-0.4	-0.1645	-1.0
6. Reference group = *EU*								
7. *RW*					0.4895	4.3*	0.4458	3.6*
D. University of first job								
1. *Top 10 U.S.*					0.1578	1.8	0.1500	1.7
2. *Next* 15 *U.S.*					0.0754	0.7	0.0718	0.7
3. *Next 27* U.S.					-0.0544	-0.5	-0.0500	-0.5
4. *Other U.S.*					-0.1078	-0.9	-0.1092	-0.9
5. Reference group = *EU* + Missing								
6. *RW*					-0.1256	-1.2	-0.1468	-1.5
7. *Missing*					-1.5645	-3.5*	-1.5659	-3.4*
E. Current job in 2007								
1. *Top 10 U.S.*					1.1140	9.9*		
2. *Next* 15 *U.S.*					0.5955	5.0*		
3. *Next 27* U.S.					0.1529	1.6		
4. Reference group = *OSC*								
F. Current job & Geographic mobility								
1. *Top 10 U.S., Stayers*							1.0896	4.6*
2. *Top 10 U.S., Foreigners*							1.2808	7.9*
3. *Next 15 U.S., Stayers*							0.5648	2.4*
4. *Next 15 U.S., Foreigners*							0.7600	4.7*
5. *Last 27 U.S., Stayers*							0.0191	0.1
6. *Last 27 U.S., Foreigners*							0.4533	3.2*
7. *OSC, Brain circulation*							0.2338	1.89
8. Reference group = *OSC, Stayers*								
9. *OSC, Foreigners*							0.2076	1.7
N	2,530		2,530		2,530		2,530	
Adjusted-R^2	0.057		0.436		0.554		0.557	

Table 2.A. Two regression models for the total sample

Dependent variable: Log *Q*

KEY COVARIATES	MODEL 3' Coeff.	MODEL 3' *t*-value		MODEL 4' Coeff.	MODEL 4' *t*-value
1. *Top 10 U.S., Male*	1.1079	9.6*	*Top 10 U.S., Stayers*		
			1. *Male*	0.9993	4.2*
			2. *Female*	0.8248	2.9*
2. *Top 10 U.S., Female*	0.8092	5.1*	*Top 10 U.S., Foreigners*		
			3. *Male*	1.2229	7.8*
			4. *Female*	0.8034	2.8*
3. *Next 15 U.S., Male*	0.5644	4.9*	*Next 15 U.S., Stayers*		
			5. *Male*	0.4864	2.1*
			6. *Female*	0.1592	0.7
4. *Next 15 U.S., Female*	0.1869	1.1	*Next 15 U.S., Foreigners*		
			7. *Male*	0.6931	4.5*
			8. *Female*	0.2669	1.0
5. *Last 27 U.S., Male*	0.1688	1.8	*Last 27 U.S., Stayers*		
			9. *Male*	0.0256	0.1
			10. *Female*	-0.8789	-3.2*
6. *Last 27 U.S., Female*	-0.5152	-3.5*	*Last 27 U.S., Foreigners*		
			11. *Male*	0.3901	2.7*
			12. *Female*	-0.0475	-0.2
7. Reference group = *OSC, Male*	-	-	*OSC Brain circulation*		
			13. *Male*	0.1993	1.5
			14. *Female*	-0.2243	-1.3
8. *OSC, Female*	-0.5967	-4.4*	*OSC, Stayers*		
			15. Reference group = *Male*	-	-
			16. *Female*	-0.8931	-4.6*
			OSC, Foreigners		
			17. *Male*	0.1300	1.1
			18. *Female*	-0.2243	-1.3
Constant	2.0184	11.6*		1.9752	10.8*
N	2,530			2,530	
Adjusted-R^2	0.555			0.561	

Table 2.B. Estimated gender productivity gaps = average male productivity – average female productivity in each cell

	MODEL 3' Gap	MODEL 3' *p*-value		MODEL 4' Gap	MODEL 4' *p*-value
1. *Top 10 U.S. departments*	0.2987	(0.054)	1. *Top 10 U.S., Stayers*	0.1745	(0.362)
			2. *Top 10 U.S., Foreigners*	0.4195	(0.063)
2. *Next 15 U.S. departments*	0.3775	(0.003)	3. *Next 15 U.S., Stayers*	0.2272	(0.002)
			4. *Next 15 U.S., Foreigners*	0.4262	(0.058)
3. *Last 27 U.S. departments*	0.6840	(0.000)	5. *Last 27 U.S., Stayers*	0.9045	(0.000)
			6. *Last 27 U.S., Foreigners*	0.4376	(0.027)
4. *29 OSC departments*	0.5967	(*t*-value = -4.4)	7. *OSC, Brain circulation*	0.4236	(0.039)
			8. *OSC, Stayers*	0.8931	(*t*-value = -4.6)
			9. *OSC, Foreigners*	0.3543	(0.009)

Table 3.A. Overall gender productivity gap. A sequence of models for the elite

Dependent variable: Log *Q*

	MODEL 1 Coeff.	MODEL 1 *t*-value	MODEL 3 Coeff.	MODEL 3 *t*-value		MODEL 3' Coeff.	MODEL 3' *t*-value
Female	-0.2437	-4.3*	-0.1578	-3.6*		-	-
Constant	6.4266	162.9*	5.4305	24.4*		5.4424	24.5*
CONTROL VARIABLES							
A. Demographic variables							
1. *Age*			0.0454	3.3*		0.0451	3.3*
2. Age^2			-0.0004	-1.96*		-0.0004	-1.94
3. *Young* x *Age*			0.0076	0.3		0.0086	0.3
4. *Young* x Age^2			-0.0002	-0.2		-0.0003	-0.2
5. *Young*			-0.0269	-0.3		-0.0359	-0.4
B. University of B.A.							
1. *Top 25 U.S.*			0.0144	0.4		0.0160	0.4
2. *Other U.S.*			-0.0893	-1.9		-0.0844	-1.8
5. Reference group = *Other countries*			-	-		-	-
C. University of Ph.D.							
1. *Harvard* & *MIT*			0.1506	3.3*		0.1492	3.3*
2. *Other Top 10 U.S.*			-0.0790	-2.0*		-0.0808	-2.0*
3. Reference group = *Rest of U.S. and other countries*			-	-		-	-
D. University of first job							
1. *Top 10 U.S.*			0.0059	0.1		0.0083	0.2
2. *Other U.S.*			-0.0522	-1.2		-0.0488	-1.1
5. Reference group = *Other countries*			-	-		-	-
E. Current job in 2007							
1. *Top 10 U.S.*			0.3590	5.3*	*Top 10 U.S.*		
					1. *Male*	0.3590	5.2*
					2. *Female*	0.0995	1.3
2. *Next 15 U.S.*			0.0763	1.6	*Next 15 U.S.*		
					3. *Male*	0.0631	1.3
					4. *Female*	-0.0109	-0.1
3. *Last U.S.*			-0.0189	-0.4	*Last 27 U.S.*		
					5. *Male*	-0.0289	-0.6
					6. *Female*	-0.1109	-1.0
4. Reference group = *OSC*			-	-	*OSC*		
					7. Reference group = *Male*		-
					8. *Female*	-0.2758	-2.6*
N	832		832			832	
Adjusted-R^2	0.012		0.327			0.329	

Table 3.B. Estimated gender productivity gaps in Model 3'

1. *Top 10 U.S. departments*	0.2595	(0.000)
2. *Next 15 U.S. departments*	0.0740	(0.301)
3. *Last 27 U.S. departments*	0.0820	(0.442)
4. *29 OSC departments*	0.5967	(*t*-value = -2.6)